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Agent-Based Support for Collaborative Data Mining in Systems Management

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Abstract

This paper addresses the issues of structuring and supporting the collaborative data mining process. It extends the technology of multiparticipant decision making support into the data mining process and describes perspective agent-based support architecture for the data mining committees. The proposed architecture is based on the agents-facilitators integrated with layered structure of case-based reasoning memory and artificial neural network to support collaborative classification and linkage analysis between the heterogeneous views of system managers. The telecommunications management example is used to illustrate the approach.

1. Introduction

Collaborative Data Mining (CDM) [1] is becoming increasingly important in different applications associated with large-scale systems management. Operations support for emerging satellite-wireless communications is one example where the telecommunications managers and operators communicate via a collaborative environment such as audio/video conferencing and application sharing for finding the Quality of Service (QoS) and fault management solutions. They share root cause analysis, alarm correlation, and event monitoring tasks [2] by jointly searching distributed Management Information Bases (MIBs) and knowledge bases, such as Cabletron Spectrum Spectro-Rx system [3]. There is a strong need in this area for systems that would support such geographically distributed data mining dialogue, and also learn, adapt, and evolve tried solutions over time so that they can be re-used in future situations.

Consider an example: The demand for service level agreements targeted at satisfying customer requirements for access to high bandwidth connections (e.g., connections over protected rings, with economical-path routing) cannot be reliably predicted in advance. Basic issues, such as cost, often cannot be determined until the final solution is actually delivered. A distributed group of experts may be supported by routing and performance modeling algorithms; however, there is a non-structured dimension to their problem-solving that is hard to express algorithmically. Thus, there is a use for knowledge-based tools to capture and iterate new solutions. In this way, tried-and-true solutions can evolve over time into semi-automated ones, and later can migrate to intelligent systems requiring minimal hands-on supervision.

The other example is telemedicine collaborative technology. The group of geographically distributed cardiovascular specialists is involved in testing the remote patient [4]. They communicate via the multipoint desktop video conferencing environment, analyzing different views of the patient's representation in the multimedia knowledge base. The views include angiograms, x-ray video, audio/video interview with the patient, patient's history text, etc. In order to identify the diagnostics patterns and guide the remote physician through the testing process there is a strong need for support tools capable of associating individual expert views and coordinating the process of mining the testing rules.

Collaborative data mining naturally serves the task of bringing the Distributed Data Mining (DDM) technology into the organizational setting. In their recent works Kargupta and his colleagues [1], [5] address the challenges and provide pilot solutions to the CDM problems. In analyzing the foundations for CDM support the authors emphasize the critical role of such techniques as integration of local data patterns into a global model, agent-based support of facilitator function, and issues of integrating learning into coordination.

This paper is focused on the agent-based architecture and coordination support for the data mining committee structures. First benefits of applying committee structures to the cooperative data mining are described in [6] where authors explore the decision tree committees. This paper is focused on collaborative data mining models that utilize committees of discriminant functions [7],[8] for support of geographically distributed collaborative environments. Figure 1 illustrates the approach.

We look at known group decision support (multiparticipant) structures, support technologies [9], and promises of computerized organizational memory from the CDM perspective. The committee model is identified as a perspective multiparticipant communication model for structuring the CDM support. It allows collaborative

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behavior based on the different types of majority rules or consensus protocol [10] Correspondingly the intelligent support architecture capable of combining benefits of agent-based support with computerized organizational memory is proposed. It integrates agents-facilitators with a layered structure of case-based reasoning memory and artificial neural network to support collaborative classification and linkage analysis (association) between heterogeneous views. We use explicit representation of feedback relationships, that exist between different views, to coordinate the work of committee experts, relate heterogeneous views to shared objects, and to train the data mining support agents. Local and integrated patterns of committee members are mapped by committees of discriminant functions (filters) in the proposed artificial neural network architecture. The case-based reasoning system functions as a long-term memory. It contains an artificial neural network segment which in turn is used to coordinate and capture short-term real time data mining meeting interdependencies.

2. Projecting Group Decision Support Models: Committee Model Potential

In practice the geographically distributed data mining team will most likely be based on the different types of communication flows between the multiple participants. It seems natural, therefore, to look at perspective collaborative data mining structures using multiparticipant information processing and networking paradigm. This approach was originated in early works of Galbraith [11], and Tushman and Nadler [12] and later implemented by many researchers. Provided that in an organizational setting the multiparticipant decision making relationships [13] could take place locally or span across vertical and horizontal organizational boundaries, it seems natural to attract known topologies of local area networking and wide area networking, as well as routing, switching and multicasting metaphor to describe collaborative multiparticipant relationships.

Based on the study of two dimensions: the direction of information stream and the structure of information flows in group decision making. Marakas [10] suggests the hierarchical classification of multiparticipant decision making structures. In this classification different multiparticipant decision making dependencies are comprised of three basic models: group, team, and committee.

In the group model the structure of information flows is a mesh network. It links multiple decision-makers in a way that allows complete interaction among them.

The team model represents a more centralized pattern of a single decision-maker with no participant interaction. Several local area and wide area communication topologies could satisfy the team structure support requirements. The primary topology will be star (originally *wheel* network [10]). This topology will fit local and interdepartmental relationships. Also, bus and ring will provide chain and circle type relationships to the team members.

The third basic model is committee (Fig. 2). It combines a single decision-maker with the complete participant interaction. It allows collective behavior that is based on the different types of majority rules or consensus protocol. A combination of star and ring topologies could be used to support local and interdepartmental committee structures. The group structure respectively could be viewed as comprised of several committees.

The data mining process takes place through the implementation of such techniques as classification, association, sequencing, and clustering. Applying listed techniques in the collaborative setting would require substantial coordination in finding the relationships between heterogeneous views, clustering, and sequencing. Group multiparticipant structure will not be the most appropriate solution in this case because it relies on the mesh topology and doesn’t separate facilitator (coordinator) from the other members. Unlike it, team topology naturally allocates a role for the decision-maker (facilitator), but it lacks cooperative relationships among the members, which could be critical in the joint knowledge discovery process. From that stand point the committee model represents a reasonable compromise between the group and team multiparticipant structures. It allows a facilitator (coordinator) role and compensates for the lack of participants’ interaction that is typical for the team structure.

Based on the described consideration we respectively select a committee model for structuring the collaborative data mining process support.

3. Agent-based Environment for Collaborative Data Mining

In the group decision support literature there is an impressive list of different collaborative support and groupware technologies [14] that could be considered for adaptation to the collaborative data mining purposes. They include different types of conference rooms: electronic room (local), teleconference room (audio/video between small groups at different locations), information center (local with data base management shared views), decision room (local with decision analysis shared views), and group networking (different offices) solutions. The support environment for the group networking systems typically includes intelligent agents that are capable of capturing user/application profiles and using them to support multiparticipant structure coordination. It also includes the elements of organizational memory to provide learning and knowledge management in organizational setting.

Due to the largely distributed character of potential data mining multiparticipant structures, the group networking technology would be an appropriate support solution. The group networking solution is typically implemented through real-time desktop audio/video conferencing and data sharing with one participant serving as coordinator or chair. Such features provide perfect fit to the committee support requirements.

Following the earlier described communications network metaphor in defining the features for collaborative data mining model, we assume that the role of intelligent agents is not only to facilitate capturing knowledge patterns and coordination of knowledge discovery but also to facilitate direct access to the individual experts. In which case coordinated access to distributed expert knowledge becomes a part of integrated man-machine knowledge base training and evolution.

Suppose we adopt the described group networking technology, in the form of a multipoint multimedia collaborative desktop conferencing system for support of the data mining committees. What would be a perspective intelligent agent architecture for such an environment? What would be perspective memory mechanisms for coordinating collaborative data mining effort?

3.1 Agent-based architecture and coordination requirements

There is a strong indication [1] that facilitator support should be in the center of agent-based architecture for collaborative data mining. This framework matches well with the recommendations for support of collaborative telecommunications network management [15] and observations on collaborative document writing and search [16]. Another important feature of agent support for collaborative work is profiling the users. Experience with the Technology Navigator, an Internet tool that implements agents to retrieve and categorize data in the collaborative setting [17], indicates the importance of profiling in data mining.

The coordination of cooperative activities should be based on revealing interdependencies involved in the usage of common objects [18]. This would require a memory mechanism for capturing the interdependencies. The dynamics of the data mining process could be viewed as comprised of the long-term and short-term phases and correspondingly would require long-term and short-term memory layers. The long-term memory would gather data mining interdependencies from previous collaborative sessions to make informed decisions, in future sessions, regarding the knowledge patterns. The short-term memory would reflect ongoing committee performance and individual adaptation through the length of the collaborative conferencing meeting.

How could it reveal in practice? Let's take a look at telecommunications management example, the hierarchy of collaborative processes within the Telecommunications Management Network (TMN) architecture (Fig. 3).

Collaborative data mining sessions take place starting the Network Management Layer (NML) up to the Service (SML) and Business (BML) layers.

We can view each layer of the TMN hierarchy as a monitoring/reasoning/control loop making up a multi-layered architecture (MLA) [3]. Within the generic MLA each layer is a separate control loop that corresponds to a specific class of problems. The problems are partitioned and assigned to levels according to the amount of time and type of information required to solve them.

For example, the short-term abstraction/coordination/decomposition loop at the lowest level provides quick reaction, bypassing upper level control mechanisms. In the TMN domain, such tasks might include intelligent routing and temporary disconnection to a busy host. The medium-term loop provides reaction to more complex problems and operates on increasingly abstract input such as signs. Tasks of this sort might include alarm correlation in a busy network with multiple alarms, where some alarms are real and others are apparent, and the task is to distinguish the two and suppress all apparent alarms. The top level would provide reaction to problems that require more time. The classic example of a task of this kind is the reasoning involved in deciding to move a host from subnet A to subnet B because the majority of the host's clients reside on subnet B, thereby causing increased traffic on the link between A and B.

Now let us look at the TNM hierarchy in conjunction with the multi-layered architecture [2]. From the multi-layered architecture perspective each TMN layer consists of monitoring, abstraction, coordination, decomposition, and execution of control actions. At the bottom of the management hierarchy is layer 1, which is typically implemented by vendors who create communication devices. The functions are implemented as threshholding triggers or shallow rule-based systems. In practice, next layers of management, layers 2 and 3, are supported by the management systems such as Cabletron Spectrum Enterprise Management Platform. Spectrum employs a form of model-based reasoning called inductive modeling technology (IMT) to perform the functions at these two layers. Note that the coordination methods in these lower levels are mostly static and hardcoded. It is assumed that the work at lower layers has been supported by the Cabletron Spectrum systems features such as dynamic auto-discovery, event correlation, and alarm correlation, whereas at layer 4, support of dynamic learning for distributed problem-solvers is expected.

4. Agents-Facilitators for Collaborative Data Mining

In order to address the above listed requirements to perspective agent-based architecture for support of collaborative data mining we propose to integrate agents-facilitators with computerized organizational memory [19]. In the proposed system agents-facilitators are integrated with case-based reasoning memory and enable collaborators to communicate at different levels of bridges, routers and gateways, depending on which segments of case memory are involved [15]. In structuring the agents as agents-facilitators with bridging, routing, and gateway functionality we follow the evolving KQML concept of agent communication models [20]. We expand the bridging, routing, and gateway functionality into agents integration with case memory. This enables agents-facilitators to integrate profile-based filtering and notification functionality (which is typical for intranet agents) with case-based reasoning search for collaborative data mining support resources (Fig. 4).

5. Long-term Coordination: CBR Memory Model of CDM Feedback Relationships

In order to structure the long-term memory for the data mining process we need to find a format for mapping collaborative data mining events. A simple event history list would require much overhead by the users to sort through the events in order to piece together relationships and reconstruct a cohesive event history surrounding one particular task, such as linkage analysis (association). The model we propose involves compressing the representation of a task or of components of a task by relating the events through the feedback control structure [19]. Such a compressed representation is easier for users to learn because it requires less load on the memory to associate the events [21].

6. Short-term Coordination: Learning Committee's Experience by ANN

Suppose that a geographically distributed collaborative desktop teleconferencing meeting for classifying the new problem (i.e. root cause for the packet loss in the inter-satellite link) has started. It is a short-term phase of the data mining process. Suppose that each committee member is communicating with others via the agent-facilitator (i.e. agent-router), and agents are mapping the expert's knowledge of classifying the causes into the described CBR memory. In order to observe the real time collaborative data mining process (vs. asynchronous) and to capture the results of resolving different views on causes classification, we will obviously need to add a short-term learning structure that agents can use to classify the event on behalf of the members. It appears that if we use a set of discriminant functions to represent individual classifiers, the short-term learning representation of committee collaborative experience could be structured in the form of 4 layered artificial neural network.

6.1 Telecommunications Management Example: System Diagnosis

In order to illustrate the approach let us go back to the example of collaborative data mining in telecommunications network management. Suppose that a committee of TMN managers is involved in the process of system performance diagnosis. Experts are located at geographically distributed centers, and the subject for the collaborative data mining session is to find solutions for fault/performance management. Management of high-speed telecommunications, like SONET/ATM networks is one such example. In order to monitor SONET/ATM network performance, the network manager can examine the data flows remotely by looking at data, analyzing the protocol, and collecting statistics [23]. It is unlikely that complete statistics will be collected for every ATM virtual channel connection, and the manager would look for advice from other experts on how to classify mixed performance patterns. Testing of virtual paths and virtual connections in ATM network fault management requires virtual test signals: special cells that carry administration and maintenance commands and statistics. Defining these cells represents a challenge for a single person and requires collaboration with the other experts. Suppose that committee is trying to classify the controls for restoring the quality in IP over ATM connection:

6.2 Discriminant Functions for Collaborative Classification

One way to formalize this classification problem would be to use the discriminant functions for mapping the individual committee member view of system diagnosis. Under typical malfunction conditions the diagnostic problem is to determine which parameters ($\Delta\, \underline{\mathbf{P}}$) have been affected that would explain the change in the system ($\Delta\, \underline{\mathbf{S}}$) which is assumed to be observable [24].

Assume that the system model is a system of **m** linear inequalities of the form

$$\Delta \mathbf{s} - \underline{\boldsymbol{\delta}} \leq \mathbf{C} \cdot \Delta \underline{\mathbf{S}} \leq \Delta \mathbf{s} + \underline{\boldsymbol{\delta}} \qquad (1)$$

and **n** linear inequalities of the form

$$-\underline{\boldsymbol{\varepsilon}} \leq \Delta\underline{\mathbf{P}} \leq \underline{\boldsymbol{\varepsilon}} \qquad (2)$$

where $\Delta\underline{\mathbf{P}}$ is a vector of **n** parameter variations with respect to nominal values, $\Delta\,\underline{\mathbf{S}}$ is a vector of **m** measurable state variables with respect to nominal values, **C** is a sensitivity matrix, and measurement errors and parameter tolerances are modeled by vectors $\underline{\boldsymbol{\delta}}$ and $\underline{\boldsymbol{\varepsilon}}$ respectively. Formally a set of parameters $\underline{\mathbf{P}}$ is a diagnosis, if and only if all terms in system (1) corresponding to the members of $\underline{\mathbf{P}}$ are outside the intervals represented by (2) in a solution $\Delta\underline{\mathbf{P}}_0$ of (1). A possible way of modeling group preference structure is through a discrimination model.

If the observed combination of $\{\Delta p_{ik}\}_1^n$ values is judged acceptable (such as admitting additional hop for the videoconference call path without an immediate bandwidth adjustment), then the inequality is set up to be negative. If an expert (*e.g.,* a network manager/operator) evaluates this vector as indicating that bandwidth adaptation is necessary, then a non-negative value is set up. The expert responses consolidated during collaborative data mining meeting would constitute an integrated system of the form:

$$\begin{aligned} &\sum_{j=1}^{n} (W_{ij} \times \Delta p_{ij}) \geq 0 \\ &\sum_{j=1}^{n} (W_{ij} \times \Delta p_{ij}) < 0 \end{aligned} \qquad (3)$$

Solution vector $\mathbf{W=\{W_{ij}\}}$ for system (3) is used to identify the filter, as a discriminant linear function:

$$\mathbf{W_i \; x \; \Delta P_i \geq 0} \qquad (4)$$

Using the telecommunications management example it could be interpreted as follows. In many cases, the same training vector $\mathbf{\Delta P_i}$ could be evaluated as satisfactory for continuing transmitting video stream, but at the same time be evaluated as requiring bandwidth adjustment for the voice stream. This would create conflicting constraints in system (3) and would result in a state of infeasibility. When system (3) becomes infeasible, it is not possible to identify a single discriminant function (4). It is possible though to design the artificial neural network that could be trained to learn how to resolve such cases of infeasibility.

6.3 Modeling Committee Learning in Artificial Neural Network

In general, infeasibility analysis begins by isolating a feasible portion of the infeasible model. In practice, more than one form of isolation may be required. The facilitator would lead the committee in the process of trade-offs toward a non-empty feasible set.

There are two known models of isolating a portion of infeasible model that would allow for the committee to compromise on changing the boundaries for discriminant functions: minimal infeasible [25] and maximal feasible subsystems [8].

Committee models of discriminant functions [7] could be especially useful as models for coordinating committee based collaborative data mining. A committee of solutions is a finite or infinite set of elements, such that each constraint is satisfied by a majority of its members.

The hierarchical structure of discriminant functions capable of learning changes in the $\mathbf{W_i}$ coefficients is represented via the following four-layer artificial neural network:

Input layer

The *input layer* represents the learning vector $\mathbf{\Delta P_I}$, in which each input node stands for an aspiration-reservation interval for a single constraint $[RL_k, AL_k] = \Delta p_k$ (*e.g.,* loss ratio interval, jitter interval, etc.)

First hidden layer

The first hidden layer represents the discriminant functions for the revisions $\{\Delta p_k\}$ that experts evaluate as "good" or "bad" , classifying solutions with no contradiction. Each of the nodes in the *first hidden layer* represents *one* linear discriminant function $\mathbf{W_i \; x \; \Delta P_i \geq 0}$ that exactly separates "good" and "bad " revisions of $\{[RL_k, AL_k]\}$ intervals. Weights $\mathbf{w_{ij}}$, which are the coefficients of discriminant functions, are subject to changes in the process of training and are determined as feasible solutions for a system of constraints in a training sequence (6).

Second hidden layer

Nodes of the *second hidden layer* match the training cases in which revisions of $\{[RL_k, AL_k]\}$ intervals for the shared constraints are conflicting (*e.g.,* patterns of "good" and "bad" QoS are overlapping). In this case, the set of training constraints is infeasible. Each of the nodes in the second hidden layer represents a committee of discriminant functions. This is a committee of solutions, where the set of weight vectors satisfies more than half of the inconsistent constraints in the system. More precisely, each node of the second hidden layer has a threshold function:

$$F(\underline{w}) = \mathbf{\sum_k sign\,(\underline{W}_{k,*}\,\Delta\underline{P})} \qquad (5)$$

where $\mathbf{sign\,(.) = \{1,0\}}$. If $F(\underline{w}) > \mathbf{(m+1)_*r}$, where **m** is the number of members in the committee $\underline{\mathbf{w}} = [\underline{\mathbf{w}}_1, ..., \underline{\mathbf{w}}_k, ..., \underline{\mathbf{w}}_p]$, and **r** is the ratio of participation (usually one half). When the node fires, the adjacent vectors $\underline{\mathbf{w}}_i$ are taken as the coefficient vectors for related empirical constraints.

The selection criteria for the committee of constraints may vary. In the case where weights are equal, the selection criterion is a simple majority rule. See [26] for more details.

7. ANN Integration with CBR Memory

For a single function filter the discriminant function (4) is placed into the short-term memory segment of the case-based memory stack (see Figure 4) that contains the associated segment of data mining task feedback relationships and also committee member profiles. Thus the real time data mining meeting events (short-term) become associated with the long-term data mining patterns via the case-based reasoning index.

When the data mining meeting begins, agent-facilitators check the observed values of $\mathbf{\Delta P}$ by plugging them into the discriminant function (4). If, for all nodes, the value of $\mathbf{W_i} \ \mathbf{x} \ \mathbf{\Delta P_i}$ is negative, the agents-facilitators inform the committee members and committee coordinator in results of classification. If some nodes vote "yes" to initial object classification, and the others vote "no", then the second layer committee nodes that indicate associations with the data mining task profile are checked. If the committee node votes "yes", then classification is accepted.

Conclusion

Collaborative data mining combines the technology of multiparticipant decision making with data mining techniques. Geographically distributed experts, engaged in data mining problem solving, will benefit from the collaborative data mining system by being able to combine their individual expertise in targeting such tasks as classification, association, sequencing, and clustering. It is a new area of study. Among the main challenges in designing a support environment for collaborative data mining are issues such as architecture of intelligent agents, coordination mechanism, and communication structure for multiparticipant work. This paper presents sample solutions for structuring data mining committees support. Solutions include agents-facilitators that are integrated with layered case-based reasoning memory and artificial neural network to support collaborative classification and linkage analysis (association) between heterogeneous views. The case-based reasoning system is used as a long-term memory, and the artificial neural network is used to coordinate and capture short-term real time data mining meeting interdependencies. Revealing feedback relationships between different views is used to structure the long-term memory and to coordinate an access to distributed human knowledge sources. Visualization of data mining patterns in case memory and their links to the neural network nodes in conjunctions with 3-D views of telecommunications management interfaces is the direction of future research.

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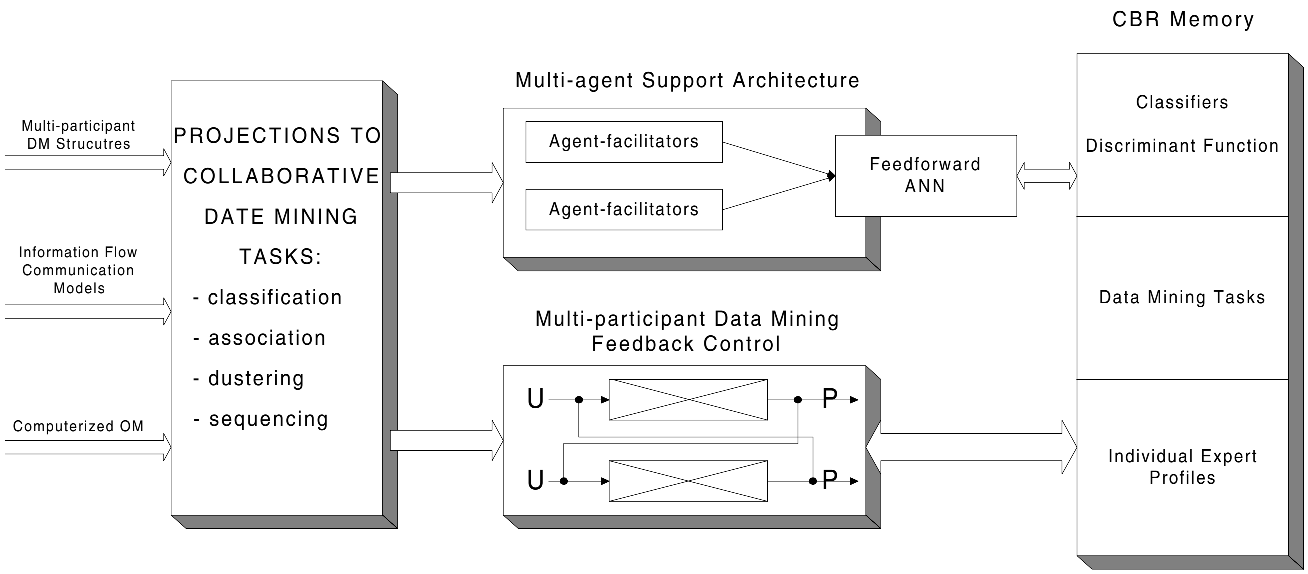

Figure 1. Agent-Based Support Environment for Collaborative Data Mining

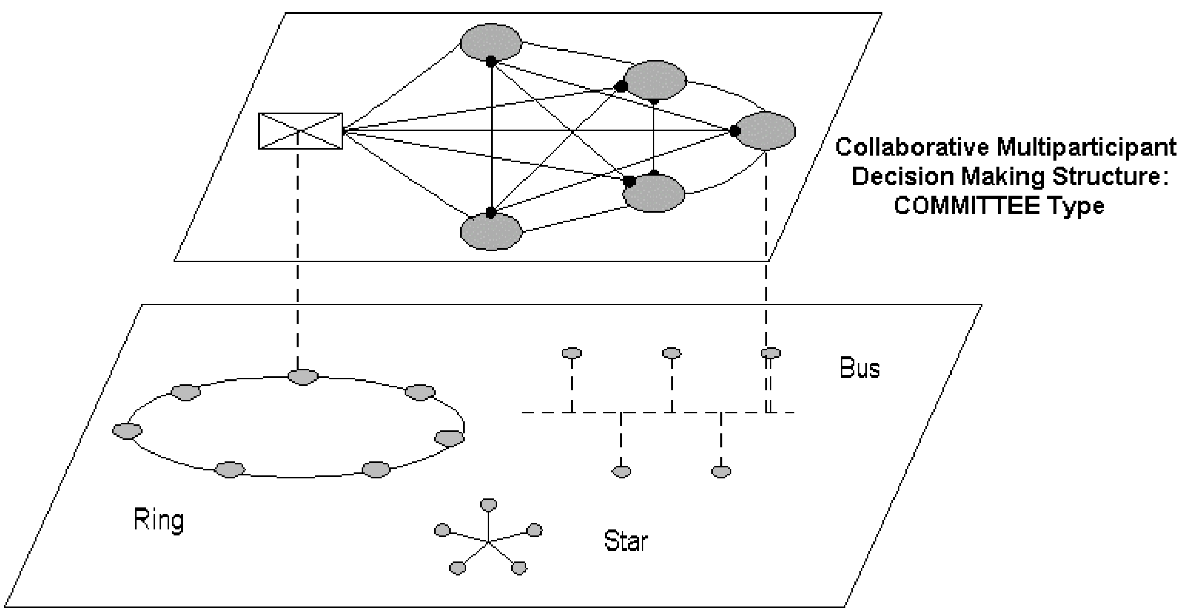

Figure 2. Committee Structure for Collaborative Multiparticipant Decision Making

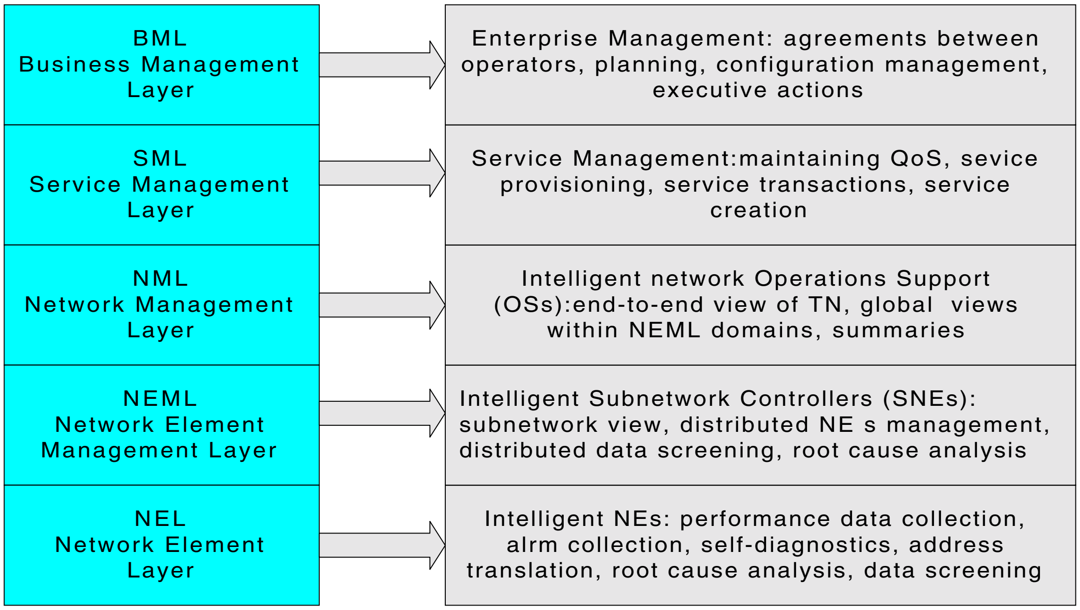

Figure 3. TMN Management Architecture

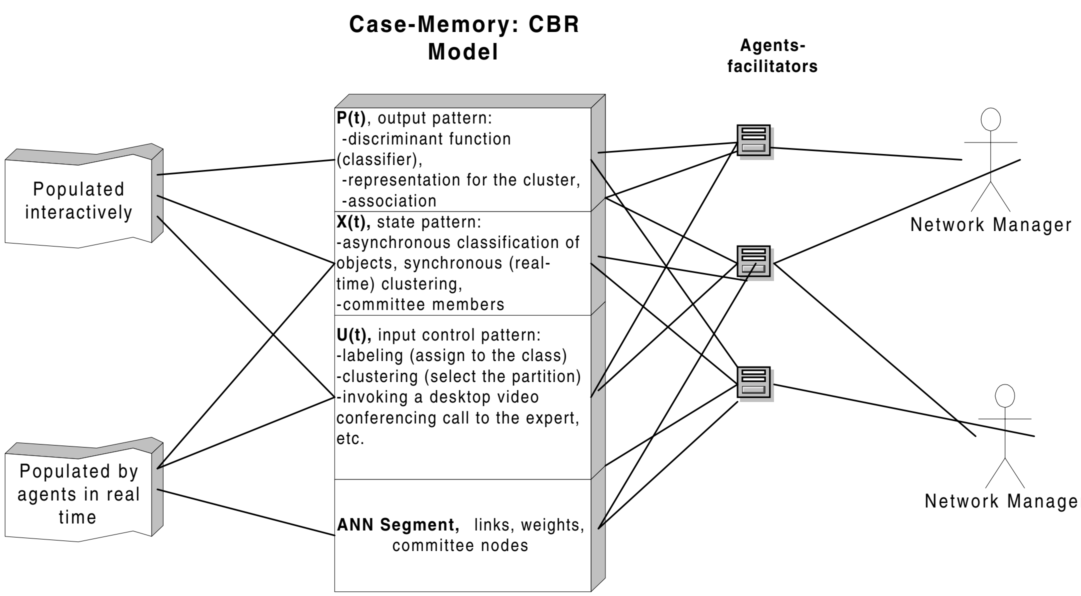

Figure 4. Agents Integration with Long-term CBR Memory and Short-term ANN Memory